Journal of Environmental Management 214 (2018) 66–75

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Characterizing, monitoring, and simulating land cover dynamics using GlobeLand30: A case study from 2000 to 2030

Jamal Jokar Arsanjani

Aalborg University Copenhagen, Department of Planning, A.C. Meyers Vænge 15, DK-2450, Copenhagen, Denmark

ARTICLE INFO

Article history:
Received 10 July 2017
Received in revised form
24 February 2018
Accepted 25 February 2018
Available online 5 March 2018

Keywords:
GlobeLand30
Historical land change
Global land cover maps
Urbanization
Desertification
Deforestation

ABSTRACT

Land cover maps provide us with a unique opportunity to monitor our environmental and anthropogenic resources over space and time. Temporal land cover maps increase the efficiency of land monitoring process by providing a set of observations so that any changes in the landscape can be tracked. So far, many land change monitoring efforts have been limited to small regions and analysing local processes, because there has been a lack of fine resolution global land cover maps for regional and global studies. Recently, the availability of bi-temporal GlobeLand30 product for years 2000 and 2010 has strengthened our land monitoring observations through a 10-year window at 30-meter resolution. The main objective of this study is to explore the land cover changes within 2000–2010 in one of the most dynamic regions in the Middle East. To do so, GlobeLand30 datasets were used for characterizing the regional landscapes and the distribution of the existing land cover types. Moreover, the study aims at predicting the future land cover patterns by 2030 based on the historical changes. The quantitative analysis reveals a high degree of changes from the majority of land types to barelands with the highest contribution from grasslands and shrublands. The vibrant spots of change are located on central Iran towards its eastern border while the persistent spots are located on its north and northwestern parts. The predictive measures using Markov chain analysis message forthcoming changes in favor of increasing barelands being taken from grasslands, cultivated lands, and shrublands. The findings are beneficial to a wide range of end users including academics, land managers, and environmentalists on a) which resources were available in the first decade of 21st century, and b) how they were treated within a decade, and c) how the resources will evolve within the following two decades. Further discussions on the achieved results and future directions of research are presented in the conclusions.

© 2018 Elsevier Ltd. All rights reserved.

1. Introduction

Continuous studies on the extent, rate, and intensity of change across different landscapes have confirmed massive land cover/use changes occurring within short periods. The changes in land cover cause various impacts in ecosystems and environmental processes at local, regional, and global scales (Symeonakis, 2016; Verburg et al., 2011). These changes appear in different forms including urbanization (Jokar Arsanjani et al., 2013; Vaz and Jokar Arsanjani, 2015; Tayyebi et al., 2013), deforestation (Pineda Jaimes et al., 2010; Seto et al., 2012), drying wetlands and water resources (Jokar Arsanjani et al., 2015a,b; Pengra, 2012; Roach et al., 2013; Gardner, 2014), desertification (Miao et al., 2016; Reynolds and Stafford Smith 2002), among others. These forms of change incorporate to the evolution and emergence of some today's environmental concerns, for instance, climate change, biodiversity loss and water/air/soil pollution (Verburg et al., 2011; López-Moreno et al., 2013). Whereas land use/cover dynamics contribute to almost 20% of global CO2 emissions, the necessity of mapping, monitoring, and modeling land cover change patterns has been flagged as a foremost importance for academia, policy makers, and stakeholders around the world (IPCC, 2007).

Earth observatories and geoinformation technologies, spatial analysis, predictive modeling techniques are now widely applied within a round cycle in order to gain a more robust and continuous observation over our resources and their dynamism (Aubrecht et al., 2009). To do so, they attempt to improve the spatial and temporal resolution of the observations so that the small changes in the landscape could be detected and studied. Though, detecting landscape changes is still a challenging task and requires considerable temporal and financial costs. To address this challenge,

E-mail address: jja@plan.aau.dk.

https://doi.org/10.1016/j.jenvman.2018.02.090
0301-4797/© 2018 Elsevier Ltd. All rights reserved.

several international and regional institutes have been trying to generate consistent and accurate global land cover maps or sampled observations points e.g., LUCAS (Gallego and Bamps, 2008) and Geo-Wiki (Fritz et al., 2009), OpenStreetMap (Jokar Arsanjani et al., 2015a,b) for continuous monitoring of land cover so that the academics can save the time and cost of preparing the land cover maps (Friedl et al., 2002; Tchuenté et al., 2011; Giri et al., 2013; Fritz et al., 2010; Yu et al., 2018).

Traditional global land cover mapping efforts have been focused on the preparation of these maps at coarse spatial resolutions, for example, 300 m and 1000 m, for rough estimations of land cover extents. Some examples of them are GlobCover 2009 (Arino et al., 2012), IGBP DISCover (Loveland et al., 1999; Belward et al., 1999), UMD Land Cover (Hansen and Reed, 2000; Hansen et al., 2000), Global Land Cover 2000 (Bartholomé and Belward, 2005). Despite the massive efforts invested in preparing them, there is a big challenge in using them as we are not able to capture and observe local land changes at a microscopic scale. Because their resolution is simply too coarse to capture the local variation of land cover patterns. For instance, with a land cover map with 1-km resolution, the change can be flagged if the changed area is bigger than 1 km*1 km size, otherwise, the change is disregarded (Batisani and Yarnal, 2009; Fritz et al., 2011; Congalton et al., 2014).

Recently, thanks to the free availability of fine resolution satellite images including Landsat, ASTER, Sentinel, the possibility of generating global land cover maps finer than 30 m resolution is provided. However, achieving this requires tremendous efforts to invest. Because, there are some practical challenges to tackle, for instance, the problem of availability of temporally consistent global coverage of Landsat images of high quality (minimal cloud coverage, noiseless), dealing with huge volume of data, limited availability of accurate and timely training and validation samples, high performance computing requirements, as well as being largely time-consuming (Giri et al., 2013; Townshend et al., 2012; Hansen et al., 2013; Gong et al., 2013; McCallum et al., 2006; Chen et al., 2015; Grekousis et al., 2015). A few efforts towards generating multi-temporal global land cover maps at 30 m resolution based on the long-term archive of Landsat satellite images are conducted. Among them, the USGS Land Cover Institute (LCI) and National Geomatics Center of China (NGCC) under the “Global Land Cover Mapping at Finer Resolution” initiative can be noted. The latter has already released GlobeLand30 at two timestamps of 2000 and 2010. The GlobeLand30 land cover datasets are a recent release of a bi-temporal global land cover produced by the National Geomatics Center of China (NGCC). The dataset provides us with a homogenous global dataset for land cover mapping at a spatial resolution of 30 m for 2000 and 2010. They are produced based on exceeding 10,000 collected Landsat satellite images. A pixel-object-knowledge based approach was implemented to produce this data (Han et al., 2014; Chen et al., 2015), which has an overall global accuracy exceeding 80% (Chen et al., 2015). A few studies evaluated the accuracy of the data across different landscapes including the study area of this research, which message acceptable accuracy measures (Jokar Arsanjani et al., 2016a,b; Brovelli et al., 2015; Yu et al., 2018).

Therefore, GlobeLand30 can provide us with a finer lens to look at the regions vastly affected due to climate change in order to identify the forms of impact. Currently, arid areas are under a big thread, to name a few, areas in the Middle East can be mentioned that are facing continuous dust storm events across different seasons of the year (Goudarzi et al., 2014; Shahsavani et al., 2012; Cao et al., 2015; Deus and Gloaguen, 2013). Thus, in this paper, we aim to study one of the vibrant regions as identified in Section 2.1. The reasons are that this region has gone under massive environmental changes due to the recent civil wars in the region, population increase, rapid urbanization, and increasing demand for exploiting natural resources and food production. In doing so, we will be able to understand the patterns and dynamics of land cover useful for analysis of environmental quality, hydrological cycles, ecology biodiversity, and human health (Turner et al., 2007; Jokar Arsanjani et al., 2016a,b; Wang et al., 2016; Pielke et al., 2011)

The main objectives of this study are twofold: a) to identify the rates and types of land change across a selected study area, b) to explore the usefulness of GlobeLand30 for 2000 and 2010 for temporal land cover change monitoring, and also c) to examine the suitability of GlobeLand30 for future land cover modeling. Therefore, it is intended to find answers to the following research questions:

- What is the extent and pattern of land cover in the selected study in 2000 and 2010 based on GlobeLand30?
- What is the pattern and rate of land cover change within the selected study area as a highly dynamic area within 2000–2010?
- How the future land cover patterns look like e.g., by 2030? What do the findings on the future landscape imply and which messages can be delivered to end users and stakeholders?

The remainder of this paper is structured as follows: Section 2 provides an overview of the data and methodologies used in the study. Section 3 presents the findings and continued to discussions on them in Section 4. Section 5 concludes the key findings and identifies future research directions.

2. Materials and methods

2.1. Data and study area

For this study, a very dynamic area is selected, which covers a part of the Middle East covering Iran and neighboring countries. In order to achieve the objectives of this study, 11 image tiles for two timestamps of 2000 and 2010 were collected through the official online platform at http://www.globallandcover.com. The land cover nomenclature was extracted from the product's metadata and applied accordingly as shown in Table 1.

Fig. 1 shows the configuration of image tiles of GlobeLand30 used in this study.

2.2. Methods

Fig. 2 demonstrates the flowchart of the study conducted in the paper. After preparing a pair mosaic of GlobeLand30 tiles for two timestamps, a cross-tabulation analysis was conducted between the two datasets in order to identify change transition within 2000 and 2010. Thereafter, the land cover statistics were identified and historical changes were identified along with the analysis of change trend. Once the statistical analysis was carried out, a Markov chain model, which is a predictive model, was applied to generate the future estimates of land change for each land type. The target timestamp for prediction is 2030.

3. Results

3.1. Map changes

Land cover change analysis was conducted to measure the magnitude and orientation of changes between the two timestamps. The results, as shown in Fig. 3, reveal the magnitude and rate of change across different land types. In terms of net changes, three major dynamic classes are evident such as barelands

Table 1
Land cover nomenclature of GlobeLand30 (Chen et al., 2015).

Land cover code	Land cover type	Covered features in each land type
10	Cultivated Land	Lands used for agriculture, horticulture and gardens, including paddy fields, irrigated and dry farmland, vegetation and fruit gardens, etc.
20	Forest	Lands covered with trees, with vegetation cover over 30%, including deciduous and coniferous forests, and sparse woodland with cover 10–30%, etc.
30	Grassland	Lands covered by natural grass with cover over 10%, etc.
40	Shrubland	Lands covered with shrubs with cover over 30% including deciduous and evergreen shrub, and desert steppe with cover over 10%, etc.
50	Wetland	Lands covered with wetland plants and water bodies including inland marsh, lake marsh, river floodplain wetland, forest/shrub wetland, peat bogs, mangrove and salt marsh, etc.
60	Water bodies	Water bodies in the land area, including river, lake, reservoir, fish pond, etc.
70	Tundra	Lands covered by lichen, moss, hardy perennial herb and shrubs in the polar regions, including shrub tundra, herbaceous tundra, wet tundra and barren tundra, etc.
80	Artificial surfaces	Lands modified by human activities, including all kinds of habitations, industrial and mining area, transportation facilities, and interior urban green zones and water bodies, etc.
90	Bareland	Lands with vegetation cover lower than 10% including desert, sandy fields, Gobi, bare rocks, saline and alkaline lands, etc.
100	Permanent snow and ice	Lands covered by permanent snow, glacier, and icecap

(~468,000 km^2), grasslands (~255,000 km^2), and shrublands (~220,000 km^2), respectively, while the rest of classes changed comparatively less over this period. Among them, cultivated lands (~5000 km^2), forests (~500 km^2), and artificial surfaces (~400 km^2) appear to be less dynamic with a positive difference over this period meaning that their extent has grown.

Table 2 presents the cross tabulation between GlobeLand30-2000 and GlobeLand30-2010, which shows the statistics of persistence as well as losses and gains among land cover classes. Obviously, a large area of grasslands and shrublands turned into barelands. The quantity of changes is substantial as the net change towards barelands is almost the size of entire Iraq or almost ¼ of Iran. More importantly, the change of all classes to barelands means that a large amount of land has become bare or contains vegetation cover <10% or saline and alkaline lands (see Table 1), i.e., the spark of desertification processes.

With regards to the location of gains and losses, Fig. 4 presents the gains and losses in details and Fig. 5 demonstrates several maps visualizing the locations of gains and losses across main dynamic land cover types. Additionally, while a big area in central Iran towards south and east changed from grasslands and shrublands to barelands, an inverse pattern is evident in south Turkmenistan, where a big area was converted from bareland to grassland and shrubland.

A closer look at gains and losses shows that the three major dynamic classes have gains and losses, which confirms the high magnitude of dynamism within these land types. It is surprising though that the gain of artificial surfaces does not seem to be substantial within this period as opposed to the three major dynamic classes. Despite the continuous developments in the study area e.g., Iran, the Persian Gulf surrounding states and former the Soviet Union states, higher rates of changes in favor of artificial surfaces were expected. However, the net change is about 340 km^2, which is the size of half Tehran (the capital of Iran) and that is still considerable (See Fig. 3). According to Table 2, the major contributions to artificial surfaces were received from grasslands, cultivated lands, shrublands, and forests, respectively (Fig. 6a). Figure 6 demonstrates the contributions to net changes from each land type.

Fig. 6b demonstrates the contributions to net change in cultivated lands, which shows a large area of barelands and shrublands, were converted to cultivated lands followed by forests, grasslands, and water bodies. As shown in Fig. 6c, shrublands were the only contributor to the forest class with a positive balance, while the remaining classes took areas from forests. The only substantial contributor to grasslands is shrublands (Fig. 6d). While shrublands received minor contributions, it along with grasslands contributed substantially to the expansion of barelands as shown in Fig. 6e and f.

3.2. Land cover persistence versus change

Fig. 7a shows the spatial patterns of land cover change and persistence across the study area. It shows that land cover is less persistent in the center of Iran towards the east, where the western part of Pakistan and Afghanistan, as well as east Turkmenistan, is included. On the contrary, the western and north-west parts of the study area remain persistent within the study period. Using the map of eco-regions for the study area produced based on GlobeLand30 in (Jokar Arsanjani et al., 2016a,b), it is evident that eco-region 2 and 4 (dominated by barelands) have gone under the greatest changes. Eco-regions divide Earth's surface into relative homogeneous areas in terms of biotic and abiotic factors (e.g., soils, climate, physiography, vegetation, and geology) with unique boundaries based on ecosystem patterns (Omernik, 1995).

Since the bareland class was the most dynamic class with substantial gains and losses, it highlights the importance of finding the geographical distribution of the dynamics. The transition of all classes to bareland within this period is also shown in Fig. 7b.

3.3. Change trend

In order to identify the areas with high and low change density, change trend analysis module implemented in Idrisi software is conducted. As a result, hot spots and cold spots of change based on a user-defined polynomial function i.e., 3rd order as recommended by (Eastman, 2016) are identified. Fig. 8a presents a cubic trend analysis representing hot and cold spots. Since the major changes in the study area were conversion to bareland, a bareland-centric analysis was done. It can be interpreted that while north and northwestern part of the study area have gone under minor conversions to bareland, the center and east part (east Iran towards Afghanistan and Pakistan border) went under massive conversion. Fig. 8b shows that the land cover changes in favor of artificial surfaces are concentrated in the center towards north and northeast. These locations reside in big Iranian metropolitan areas including Tehran, Isfahan, Shiraz, and Mashhad with a flash on the Persian Gulf surrounding cities including Dubai, Doha. Fig. 8c shows the hot spots of expansion of farming towards the northeast of the study area within Turkmenistan. Fig. 8d demonstrates areas undergoing forestation, which lean towards the western part, where the Zagros Mountains are located.

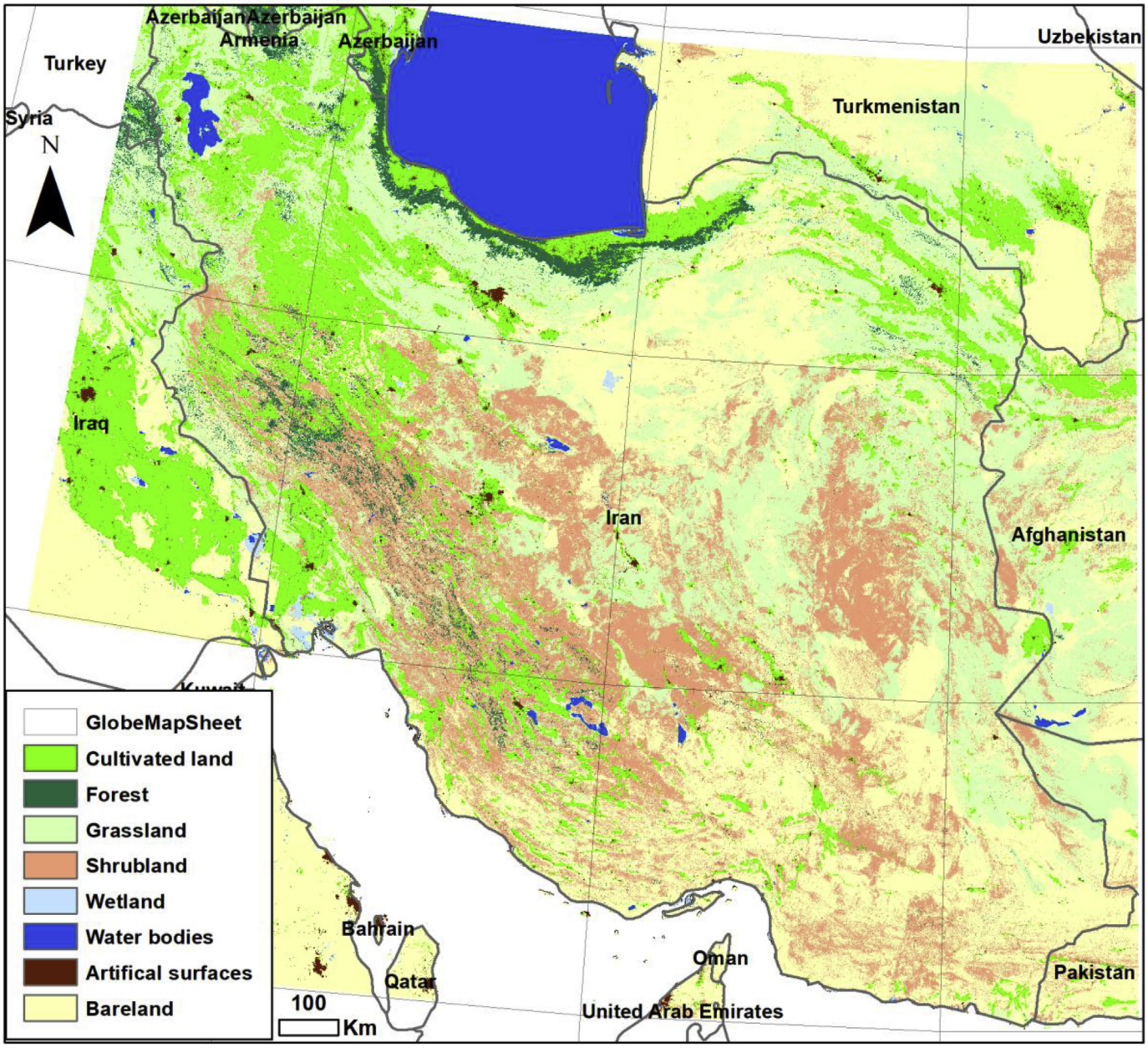

Fig. 1. Image tiles of GlobeLand30 and the study area.

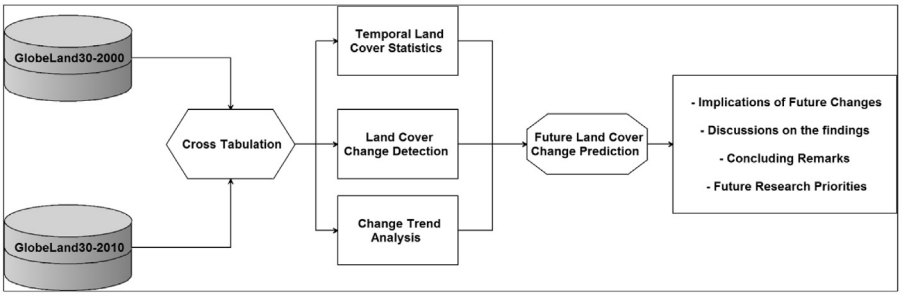

Fig. 2. Flowchart of the study.

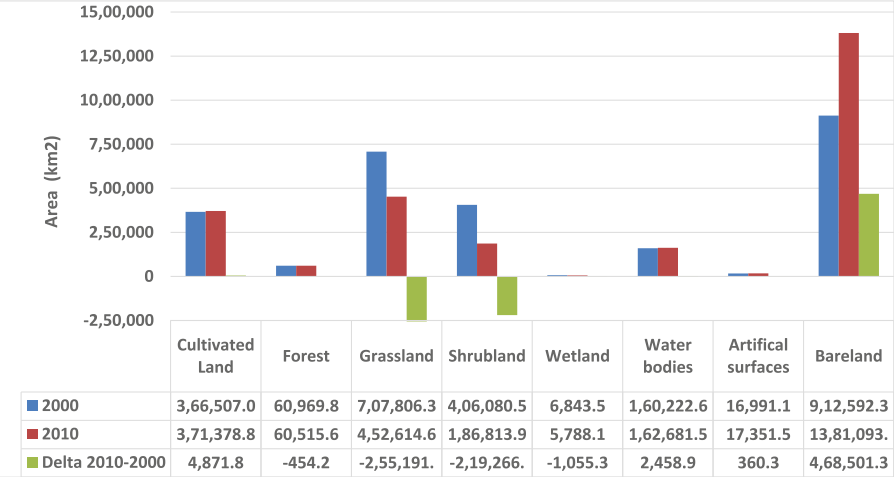

Fig. 3. Land change statistics across different land types within 2000–2010.

Table 2
Cross-tabulation of land cover data within 2000–2010 in terms of km^2.

		Areal coverage in 2000 (km^2)							
		Cultivated Land	Forest	Grassland	Shrubland	Wetland	Water bodies	Artificial surfaces	Bareland
Areal coverage in 2010 (km^2)	Cultivated Land	357,080	388	5538	2476	89	2131	498	5114
	Forest	153	53,739	1675	4180	8	11	4	750
	Grassland	5403	1873	341,797	27,217	145	221	88	75,873
	Shrubland	557	3802	15,180	136,133	23	48	23	31,044
	Wetland	38	30	113	67	4483	738	1	131
	Water bodies	364	29	281	190	873	158,641	6	2244
	Artificial surfaces	607	12	216	125	5	7	16,175	187
	Bareland	2327	1099	343,043	235,714	1122	351	188	797,221

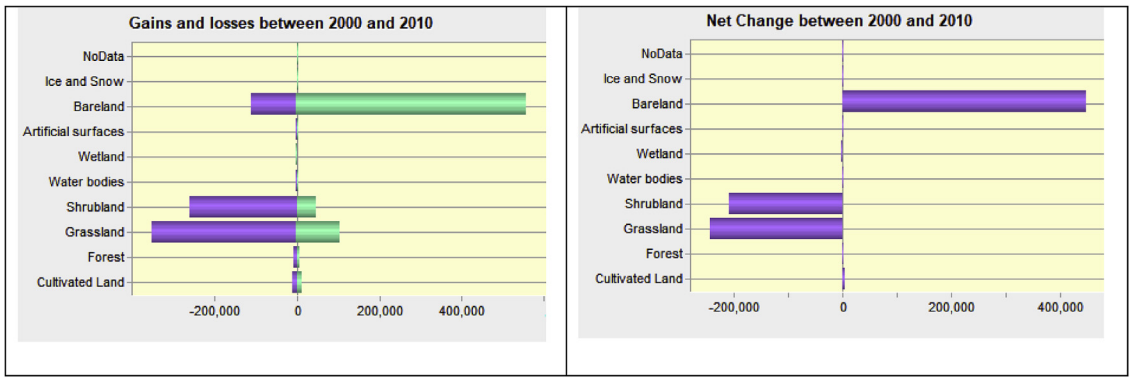

Fig. 4. (a) Trade-off between different land types i.e., green bars as gains and purple bars as losses, (b) net change within 2000–2010 in terms of km^2. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

3.4. Change prediction

Once the historical change analysis is conducted, it is possible to predict the upcoming changes in future. To do so, Markov chain analysis implanted in Land Change Modeler of Idrisi software is carried out. The Markov Chain model is a stochastic modeling approach that calculates the probability of conversion from one land type to another one. The model has been widely applied in land cover change modeling (Jokar Arsanjani et al., 2013; Jokar Arsanjani et al., 2011). The model determines the size of area vulnerable to change from each land type along with the probability values for the change, for instance, the probability of change from one category e.g., forest to another category e.g. artificial surfaces (Zhou et al., 2012; Kamusoko et al., 2009; Jokar Arsanjani et al., 2013). As a result, the transition areas matrix of change from 2010 until 2030 is generated and shown in Table 3. In other words, this table shows the expected amount of change from 2010 to 2030 in terms of km^2 based on Markov chain model for each land cover type.

Some interesting and considerable statistics can be highlighted from Table 3 as follows. 64% of cultivated lands will remain while 16% and 11% of them will convert to grasslands and barelands, respectively. Forests will retain 66% of their extent while the rest will mainly convert to shrublands (13%), barelands (9%), and

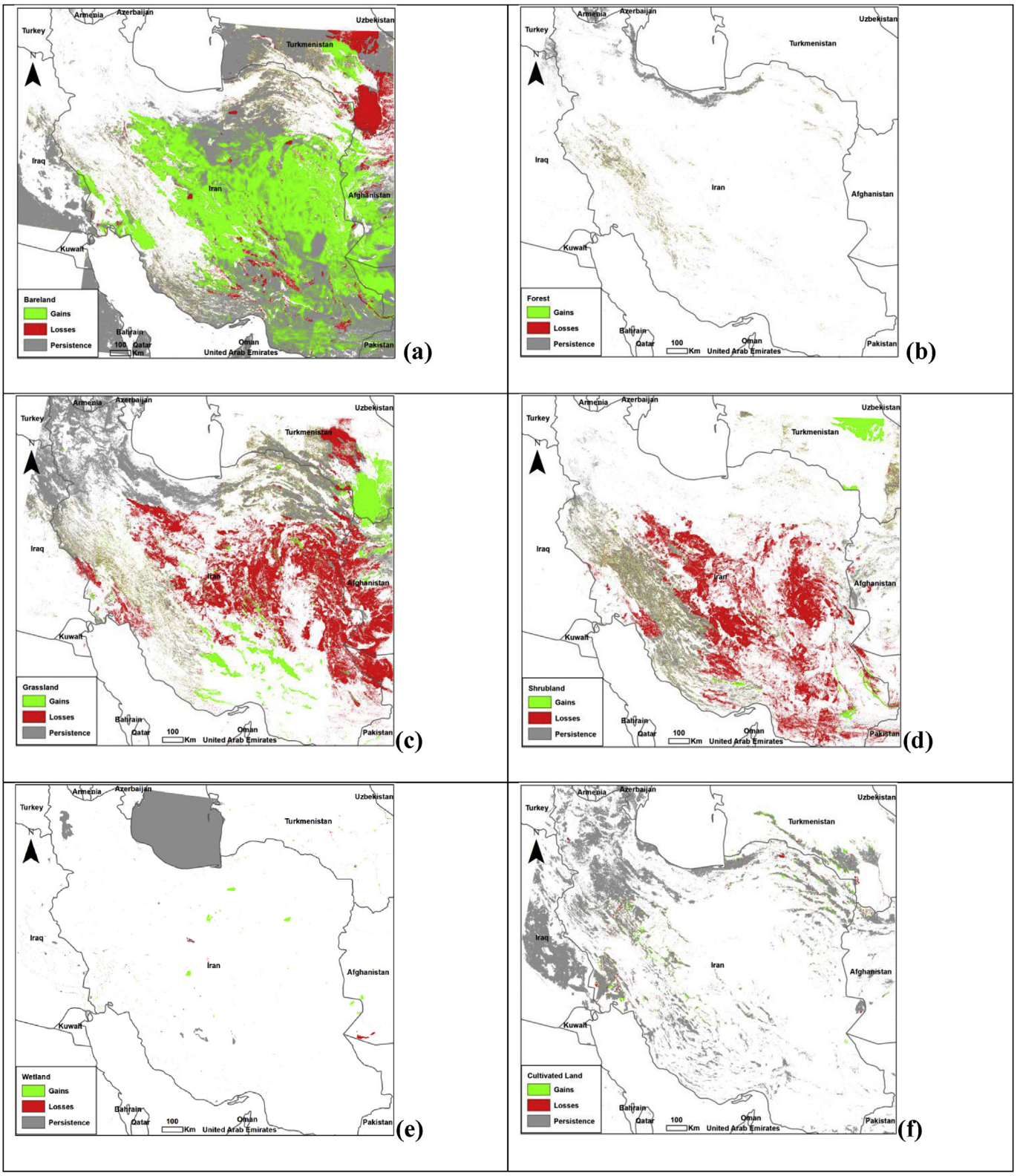

Fig. 5. Map of gains and losses in bareland (a), forest (b), grassland (c), shrubland (d), wetland (e), and cultivated land (f).

grasslands (9%). Grasslands indicate to be among the most vulnerable classes, as only 30% of their extent will remain while the rest will mainly convert to barelands (41%) and shrublands (18%). Shrublands are the other extreme vulnerable class as they will retain only 21% of their extent and 30% and 39% of their extent will turn to grasslands and barelands, respectively.

It is predicted that wetlands will lose 76% of their extent mainly in favor of water bodies, barelands, and grasslands, respectively.

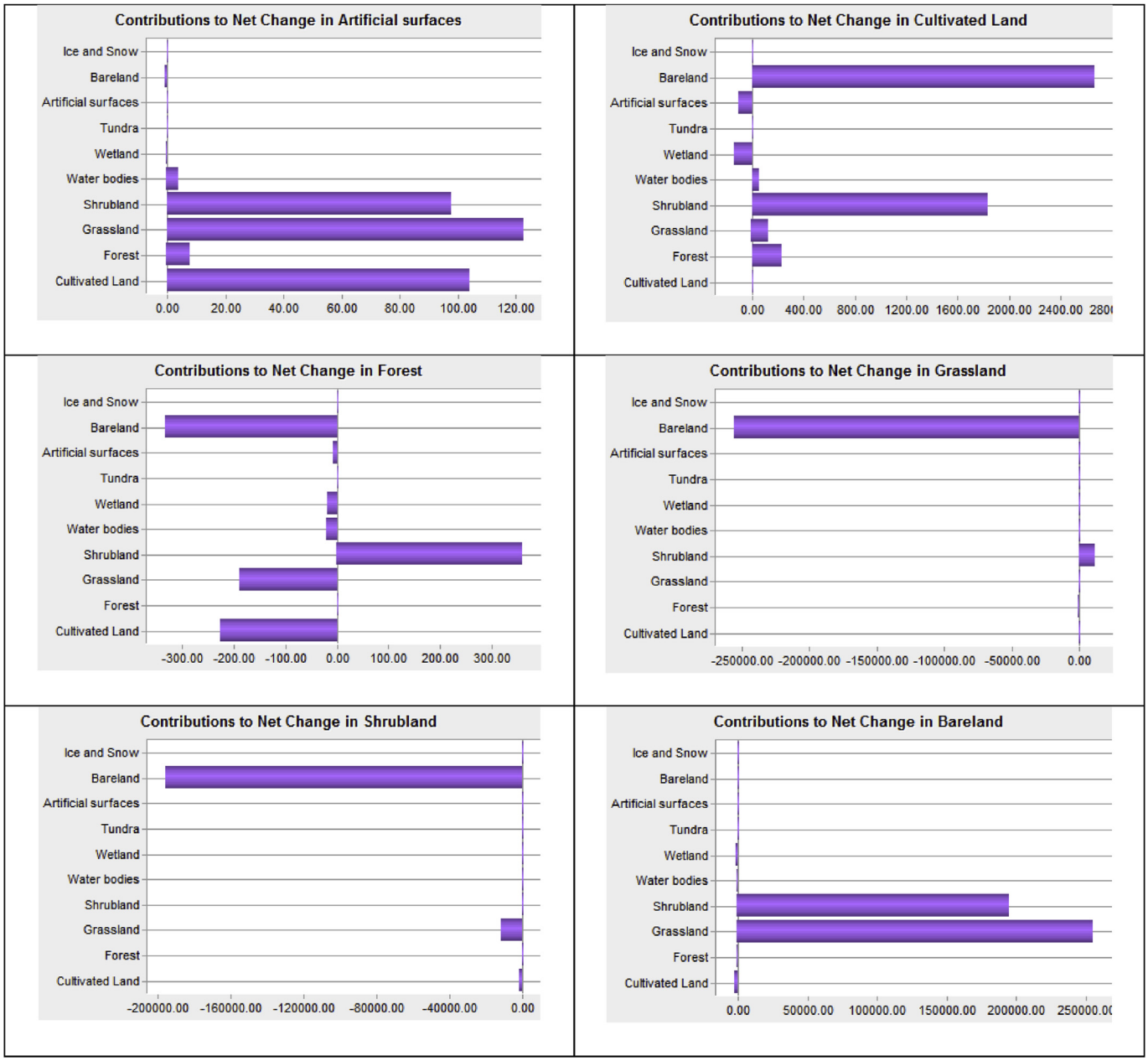
Contributions to Net Change in Artificial surfaces
Ice and Snow
Bareland
Artificial surfaces
Tundra
Wetland
Water bodies
Shrubland
Grassland
Forest
Cultivated Land
0.00 20.00 40.00 60.00 80.00 100.00 120.00
Contributions to Net Change in Cultivated Land
0.00 400.00 800.00 1200.00 1600.00 2000.00 2400.00
Contributions to Net Change in Forest
-300.00 -200.00 -100.00 0.00 100.00 200.00 300.00
Contributions to Net Change in Grassland
-250000.00 -200000.00 -150000.00 -100000.00 -50000.00 0.00
Contributions to Net Change in Shrubland
-200000.00 -160000.00 -120000.00 -80000.00 -40000.00 0.00
Contributions to Net Change in Bareland
0.00 50000.00 100000.00 150000.00 200000.00 250000.00

Fig. 6. Contribution of net change in artificial surfaces (a), cultivated land (b), forest (c), grassland (d), shrubland (e), and bareland (f).

This raises a big alarm towards protecting grasslands, shrublands, and wetlands to be converted to barelands. Water bodies appear to be one of the most sustainable classes, however, still the predictions estimate almost 8% and 5% of them to convert to wetlands and barelands as studied in (Jokar Arsanjani et al., 2015a,b), for example. The estimates show the artificial surfaces to receive contributions from cultivated lands (13%), barelands (5%), and grasslands (3%). Barelands as the most dynamic land type will receive contributions from grasslands (37%), shrublands (21%), and cultivated lands (6%). However, it is predicted that barelands will contribute to the expansion of grasslands, shrublands, and cultivated lands with 37%, 21%, and 7% of their extents, respectively.

4. Discussions

This study has explored the land changes within 2000–2010 in one part of the Middle East as one of the highly dynamic regions on our planet. To do so, GlobeLand30-2000 and GlobeLand30-2010 datasets were used for characterizing the global landscapes and the distribution of different land cover types across the region. Furthermore, the study provided predictive measures of the future land cover patterns by 2030 based on the historical changes. The findings are beneficial to a wide range of end users including academics, land managers, and environmentalists to a) discover what and how much resources are available in the study area, b) how intensive the changes emerged and evolved within the first decade into 21st century, c) what emerging land change patterns call for urgent attention in order to determine their underlying causes as well as the forthcoming consequences.

The land cover change analysis of this study proved a high degree of dynamism across different land types with least persistence in the center of Iran towards the east, where the western part of

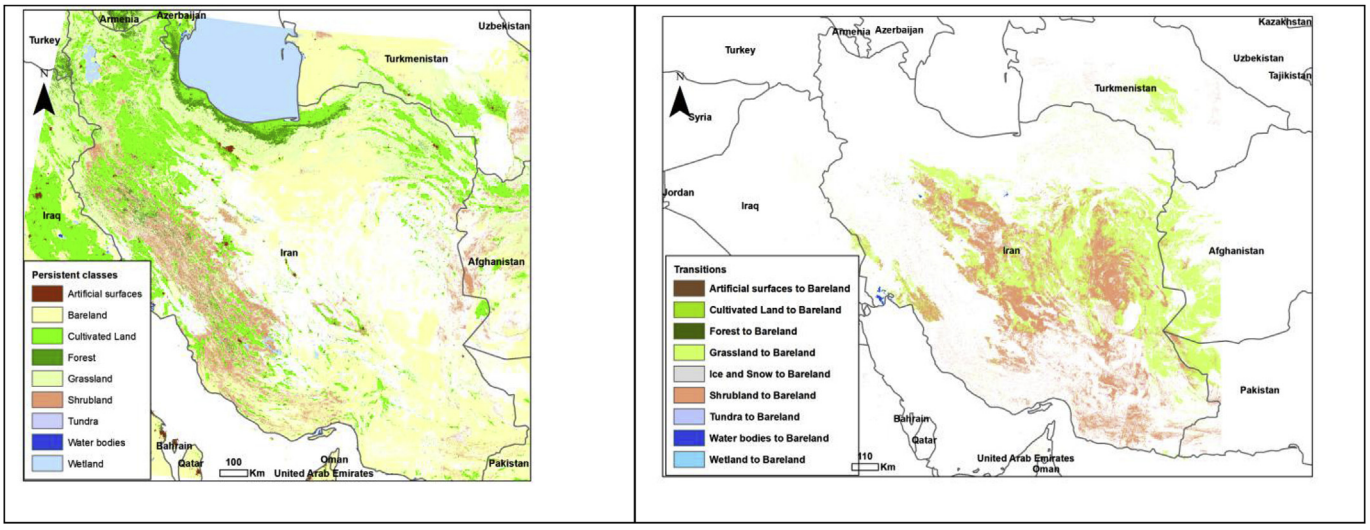

Fig. 7. a) Map of land cover persistence within 2000–2010, b) Transition from all classes to bareland within 2000–2010.

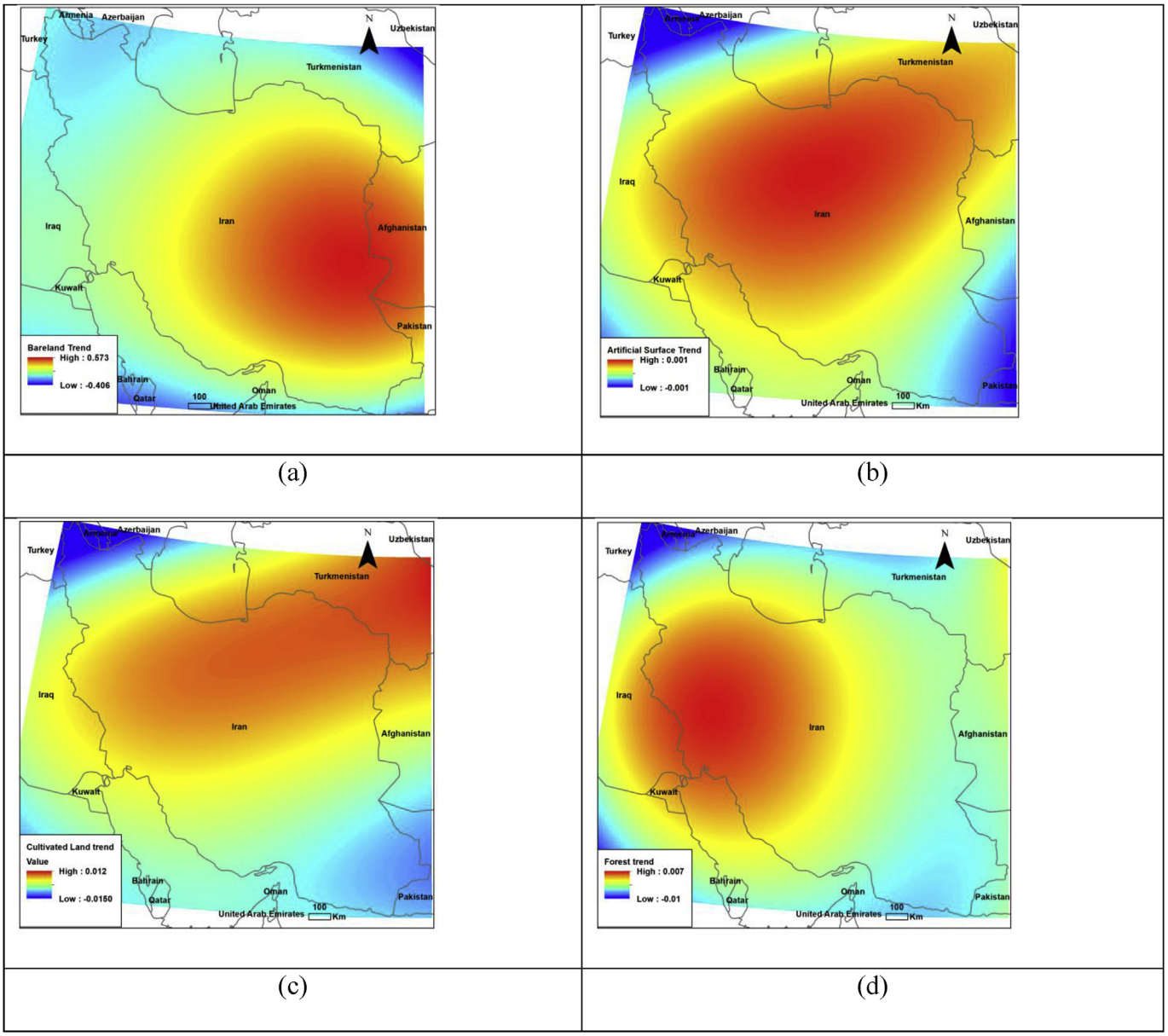

Fig. 8. Cubic trend of change towards bareland (a), artificial surfaces (b), cultivated land (c), forest (d).

Table 3
Transition areas matrix of change from 2010 to 2030 resulted from Markov chain analysis.

		Areal coverage in 2030							
		Cultivated Land	Forest	Grassland	Shrubland	Wetland	Water bodies	Artificial surfaces	Bareland
Areal coverage in 2010	Cultivated Land	47,772.1	553.6	12,339.1	2694.2	108.0	1117.6	1734.2	8396.7
	Forest	1285.1	40,069.1	5386.2	7959.3	77.1	127.8	49.5	5565.4
	Grassland	10,914.8	3383.1	47,205.9	28,315.6	217.9	1525.8	502.4	6,3674.5
	Shrubland	4595.3	4448.6	33,916.5	23,371.0	110.8	888.1	227.0	43,519.2
	Wetland	168.7	19.1	552.1	240.6	2108.7	1344.5	9.7	1157.5
	Water bodies	1718.5	107.6	1956.3	660.0	4917.2	52,049.4	63.9	2912.4
	Artificial surfaces	2305.9	26.7	591.5	204.6	4.4	43.6	13,368.3	788.7
	Bareland	11,653.4	3164.6	68,477.6	38,363.8	287.7	4098.0	519.4	59,715.8

Pakistan and Afghanistan as well as east Turkmenistan. In particular, three major dynamic classes including barelands, grasslands, and shrublands went through massive changes with almost one million cells (30 m*30 m). While the rest of classes changed comparatively less over this period, for instance, cultivated lands, forests, and artificial surfaces appear to be less dynamic. To be more specific, a large area of grasslands and shrublands turned into barelands. These change statistics are extremely surprising, because a) the net change towards barelands is almost the size of the whole country of entire Iraq, and b) the change of all classes to barelands means that a large amount of land is bare or contains vegetation cover <10% or saline and alkaline lands.

The expansion of artificial surfaces within this period does not seem to be large despite the continuous developments in the study area e.g., Iran, the Persian Gulf surrounding states and former Soviet Union states. Moreover, the contribution of water bodies and wetlands to artificial surfaces could be seen as a process of drying out them for urban developments including coastal cities across the Persian Gulf states e.g., United Arab Emirates, Qatar, Bahrain (Nassar et al., 2014; Gardner, 2014).

Given the geographic location of the study area and the recent extreme climate change impacts on this region due to a series of civil wars, this raises huge concerns on the extreme and rapid landscape change over a decade time. It should be noted that if this change rate and type continues, there will be massive environmental consequences on the human populations and socioeconomic fluctuations on the region. This is also proved by predicting the future changes through Markov chain analysis. As a result, the transition areas matrix of change from 2010 until 2030 reveals some interesting and considerable statistics. It is predicted that 64% of cultivated lands remain while 16% and 11% of them will convert to grasslands and barelands, respectively. Forests retain 66% of their extent while the rest will convert mainly to shrublands (13%), barelands (9%), and grasslands (9%). Grasslands seem to be among the most vulnerable classes, as only 30% of their extent will remain while the rest will mainly convert to barelands (41%) and shrublands (18%). Shrublands are the other extremely vulnerable class as it will retain only 21% of its extent and 30% and 39% of the extent will turn to grasslands and barelands, respectively. Wetlands will lose 76% of their extent mainly in favor of water bodies, barelands, and grasslands, respectively. This raises a big alarm towards protecting grasslands, shrublands, and wetlands to be converted to barelands. Although water bodies seem to be a sustainable class, still the predictions estimate almost 8% and 5% of them to convert to wetlands and barelands as studied in (Jokar Arsanjani et al., 2015a,b), for example.

The main concern lies in the fact that this rate of change occurred within only 10 years and if this is going to continue at the same rate, if not higher, overwhelming landscape changes must be expected. In terms of the predictive analysis used in this study, a simple and straightforward method was used while we call for more advanced methods along with exploring explanatory variables for discovering the underlying driving factors.

5. Conclusions

GlobeLand30 as the first global fine resolution and multitemporal land cover product with a 10-year interval provides a great opportunity to monitor the earth dynamics within 2000 and 2010. Its fine spatial resolution makes a finer lens for capturing the land dynamics and study their magnitude, causes, and consequences. Therefore, a wide range of applications can be presumably built based on it. Our results and conclusions are drawn based on GlobeLand30 datasets and might differ from other data sources. This is normal as a) different classification methods are applied for producing each dataset, b) dissimilar classification nomenclatures with different land type explanation are implemented, c) different spatial resolution and temporal coverage are existent, among others, and d) dissimilar quality measures for each dataset e.g., about 80% for GlobeLand30. With respect to the quality of GlobeLand30, while its quality has been tested and verified, it is recommended to contribute to the improvement of its accuracy through the official online platform and report the false classified pixels. This helps the data producers greatly to improve the quality of this dataset continuously. Other exemplary collaborative efforts based on volunteers' contributions in OpenStreetMap, for instance, have reported promising and constructive results (Jokar Arsanjani et al., 2015a,b).

Land cover dynamics across limited parts of the planet have been studied, yet, a large part of the planet have not been explored in order to identify their locations and patterns along with the underlying driving factors, in particular, developing countries with limited financial and technical resources. GlobeLand30 is a fair product for achieving this so that they can monitor their landscapes in a consistent manner and develop various applications.

References

Arino, O., et al., 2012. Global land cover map for 2009 (GlobCover 2009). https://doi.org/10.1594/PANGAEA.787668. Available at:

Aubrecht, C., et al., 2009. Integrating earth observation and GIScience for high resolution spatial and functional modeling of urban land use. Comput. Environ. Urban Syst. 33 (1), 15–25. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0198971508000677. (Accessed 5 April 2012).

Bartholomé, E., Belward, A.S., 2005. GLC2000: a new approach to global land cover mapping from Earth observation data. Int. J. Remote Sens. 26 (9), 1959–1977. https://doi.org/10.1080/01431160412331291297. Available at:

Batisani, N., Yarnal, B., 2009. Uncertainty awareness in urban sprawl simulations: lessons from a small US metropolitan region. Land Use Policy 26 (2), 178–185. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0264837708000318. (Accessed 9 March 2012).

Belward, A.S., Estes, J.E., Kline, K.D., 1999. The IGBP-DIS global 1-km land-cover data set DISCover: a project overview. Photogramm. Eng. Remote Sens. 65 (9), 1013–1020.

Brovelli, M., et al., 2015. The first comprehensive accuracy assessment of GlobeLand30 at a national level: methodology and results. Remote Sens. 7 (4), 4191–4212. Available at: http://www.mdpi.com/2072-4292/7/4/4191/.

Cao, H., et al., 2015. Identification of sand and dust storm source areas in Iran. J. Arid Land 7 (5), 567–578. https://doi.org/10.1007/s40333-015-0127-8. Available at:
Chen, J., Chen, J., Liao, A., Cao, X., Chen, L., Chen, X., He, C., Han, G., Peng, S., Lu, M., et al., 2015. Global land cover mapping at 30m resolution: a POK-based operational approach. ISPRS J. Photogramm. Remote Sens. 103, 7–27. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0924271614002275.
Congalton, R., et al., 2014. Global land cover mapping: a review and uncertainty analysis. Remote Sens. 6 (12), 12070–12093. Available at: http://www.mdpi.com/2072-4292/6/12/12070/htm. (Accessed 4 November 2015).
Deus, D., Gloaguen, R., 2013. Remote sensing analysis of lake dynamics in semi-arid regions: implication for water resource management. Lake Manyara, East African Rift, Northern Tanzania. Water 5 (2), 698–727. Available at: http://www.mdpi.com/2073-4441/5/2/698/. (Accessed 18 February 2014).
Eastman, J.R., 2012. IDRISI Selva. Clark University, Worcester, MA.
Friedl, M.A., et al., 2002. Global land cover mapping from MODIS: algorithms and early results. Remote Sens. Environ. 83 (1), 287–302.
Fritz, S., et al., 2009. Geo-Wiki.Org: the use of crowdsourcing to improve global land cover. Remote Sens. 1 (3), 345–354. Available at: http://www.mdpi.com/2072-4292/1/3/345/. (Accessed 1 March 2012).
Fritz, S., et al., 2011. Highlighting continued uncertainty in global land cover maps for the user community. Environ. Res. Lett. 6 (4), 44005.
Fritz, S., See, L., Rembold, F., 2010. Comparison of global and regional land cover maps with statistical information for the agricultural domain in Africa. Int. J. Remote Sens. 31 (9), 2237–2256.
Gallego, J., Bamps, C., 2008. Using CORINE land cover and the point survey LUCAS for area estimation. Int. J. Appl. Earth Obs. Geoinformation 10 (4), 467–475.
Gardner, A.M., 2014. How the City Grows: Urban Growth and Challenges to Sustainable Development in Doha (Qatar).
Giri, C., et al., 2013. Next generation of global land cover characterization, mapping, and monitoring. Int. J. Appl. Earth Obs. Geoinformation 25 (1), 30–37. https://doi.org/10.1016/j.jag.2013.03.005. Available at:
Gong, P., et al., 2013. Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data. Int. J. Remote Sens. 34 (7), 2607–2654. https://doi.org/10.1080/01431161.2012.748992. Available at:
Goudarzi, G., et al., 2014. Particulate matter and bacteria characteristics of the Middle East Dust (MED) storms over Ahvaz, Iran. Aerobiologia 30 (4), 345–356.
Grekousis, G., Mountrakis, G., Kavouras, M., 2015. An overview of 21 global and 43 regional land-cover mapping products. Int. J. Remote Sens. January 1–27. Available at: http://www.tandfonline.com/doi/full/10.1080/01431161.2015.1093195.
Han, G., et al., 2014. A web-based system for supporting global land cover data production. ISPRS J. Photogramm. Remote Sens. 103, 66–80. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0924271614001956.
Hansen, M.C., et al., 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach. Int. J. Remote Sens. 21 (6–7), 1331–1364.
Hansen, M.C., et al., 2013. High-resolution global maps of 21st-century forest cover change. Science 342 (6160), 850–853.
Hansen, M.C., Reed, B., 2000. A comparison of the IGBP DISCover and University of Maryland 1 km global land cover products. Int. J. Remote Sens. 21 (6–7), 1365–1373.
IPCC, 2007. Climate change 2007: the physical science basis. Agenda 6 (7), 333.
Jokar Arsanjani, J., et al., 2015a. An introduction to OpenStreetMap in GIScience: experiences, research, applications. In: Jokar Arsanjani, J., et al. (Eds.), OpenStreetMap in GIScience: Experiences, Research, Applications. Springer, pp. 1–20.
Jokar Arsanjani, J., et al., 2013. Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. Int. J. Appl. Earth Obs. Geoinformation 21 (0), 265–275. Available at: http://www.sciencedirect.com/science/article/pii/S0303243411002091.
Jokar Arsanjani, J., Kainz, W., Mousivand, A.J., 2011. Tracking dynamic land-use change using spatially explicit Markov chain based on cellular automata: the case of Tehran. Int. J. Image Data Fusion 2 (4), 329–345.
Jokar Arsanjani, J., See, L., Tayyebi, A., 2016a. Assessing the suitability of GlobeLand30 for mapping land cover in Germany. Int. J. Digital Earth p.Pending.
Jokar Arsanjani, J., Tayyebi, A., Vaz, E., 2016b. GlobeLand30 as an alternative fine-scale global land cover map: challenges, possibilities, and implications for developing countries. Habitat Int. 55, 25–31.
Jokar Arsanjani, T., et al., 2015b. Spatiotemporal monitoring of Bakhtegan Lake's areal fluctuations and an exploration of its future status by applying a cellular automata model. Comput. Geosci. 78 (0), 37–43. Available at: http://www.sciencedirect.com/science/article/pii/S0098300415000266.
Kamusoko, C., et al., 2009. Rural sustainability under threat in Zimbabwe – simulation of future land use/cover changes in the Bindura district based on the Markov-cellular automata model. Appl. Geogr. 29 (3), 435–447. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0143622808000702. (Accessed 26 May 2013).
López-Moreno, J.I., et al., 2013. Impact of climate and land use change on water availability and reservoir management: scenarios in the Upper Aragón River, Spanish Pyrenees. Sci. Total Environ. (0) Available at: http://www.sciencedirect.com/science/article/pii/S0048969713010693.
Loveland, T.R., et al., 1999. An analysis of the IGBP global land-cover characterization process. Photogramm. Eng. Remote Sens. 65, 1021–1032.
McCallum, I., et al., 2006. A spatial comparison of four satellite derived 1 km global land cover datasets. Int. J. Appl. Earth Obs. Geoinformation 8 (4), 246–255.
Miao, R., et al., 2016. Soil seed bank and plant community development in passive restoration of degraded sandy grasslands. Sustainability 8 (6), 581. Available at: http://www.mdpi.com/2071-1050/8/6/581. (Accessed 28 April 2017).
Nassar, A.K., Blackburn, G.A., Whyatt, J.D., 2014. Developing the desert: the pace and process of urban growth in Dubai. Comput. Environ. Urban Syst. 45, 50–62.
Omernik, J.M., 1995. Ecoregions: a framework for managing ecosystems. George Wright Forum 12 (1), 35–51.
Pengra, B., 2012. The Drying of Iran's Lake Urmia and its Environmental Consequences. UNEP-GRID, Sioux Falls, UNEP Glob. Environ. Alert Serv. (GEAS).
Pielke, R.A., et al., 2011. Land use/land cover changes and climate: modeling analysis and observational evidence. Wiley Interdiscip. Rev. Clim. Change 2 (6), 828–850.
Pineda Jaimes, N.B., et al., 2010. Exploring the driving forces behind deforestation in the state of Mexico (Mexico) using geographically weighted regression. Appl. Geogr. 30 (4), 576–591. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0143622810000561. (Accessed 21 May 2013).
Reynolds, J.F., Stafford Smith, D.M., 2002. Do humans cause deserts. Glob. Desertif. Do Hum. Cause Deserts 1–21.
Roach, J.K., Griffith, B., Verbyla, D., 2013. Landscape influences on climate-related lake shrinkage at high latitudes. Glob. Change Biol. 19, 2276–2284.
Seto, K.C., Güneralp, B., Hutyra, L.R., 2012. Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proc. Natl. Acad. Sci. U. S. A. 109 (40), 16083–16088. Available at: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3479537&tool=pmcentrez&rendertype=abstract. (Accessed 13 July 2014).
Shahsavani, A., et al., 2012. The evaluation of PM10, PM2. 5, and PM1 concentrations during the Middle Eastern Dust (MED) events in Ahvaz, Iran, from April through September 2010. J. Arid Environ. 77, 72–83.
Symeonakis, E., 2016. Modelling land cover change in a Mediterranean environment using Random Forests and a multi-layer neural network model. In: Geoscience and Remote Sensing Symposium (IGARSS), 2016 IEEE International. IEEE, pp. 5464–5466.
Tayyebi, A., et al., 2013. Hierarchical modeling of urban growth across the conterminous USA: developing meso-scale quantity drivers for the land transformation model. J. Land Use Sci. 8 (4), 422–442. Available at: http://www.tandfonline.com/doi/abs/10.1080/1747423X.2012.675364. (Accessed 21 November 2013).
Tchuenté, A.T.K., Roujean, J.L., de Jong, S.M., 2011. Comparison and relative quality assessment of the GLC2000, GLOBCOVER, MODIS and ECOCLIMAP land cover data sets at the African continental scale. Int. J. Appl. Earth Obs. Geoinformation 13 (2), 207–219.
Townshend, J.R., et al., 2012. Global characterization and monitoring of forest cover using Landsat data: opportunities and challenges. Int. J. Digital Earth 5 (5), 373–397.
Turner, B.L., Lambin, E.F., Reenberg, A., 2007. The emergence of land change science for global environmental change and sustainability. Proc. Natl. Acad. Sci. 104 (52), 20666–20671.
Vaz, E., Jokar Arsanjani, J., 2015. Predicting urban growth of the greater Toronto area – coupling a Markov cellular automata with document meta-analysis. J. Environ. Inf. 25 (2), 71–80.
Verburg, P.H., Neumann, K., Nol, L., 2011. Challenges in using land use and land cover data for global change studies. Glob. Change Biol. 17 (2), 974–989.
Wang, J., et al., 2016. Optimization of sample points for monitoring arable land quality by simulated annealing while considering spatial variations. Int. J. Environ. Res. Public Health 13 (10).
Yu, Q., et al., 2018. GlobeLand30 shows little cropland area loss but greater fragmentation in China. Int. J. Appl. Earth Obs. Geoinformation 66, 37–45.
Zhou, D., Lin, Z., Liu, L., 2012. Regional land salinization assessment and simulation through cellular automaton-Markov modeling and spatial pattern analysis. Sci. Total Environ. 439, 260–274. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0048969712012041. (Accessed 23 October 2012).